Chemical Research in To<u>xicology</u>

Omics Approaches To Probe Microbiota and Drug Metabolism Interactions

Robert G. Nichols, Nicole E. Hume, Philip B. Smith, Jeffrey M. Peters, and Andrew D. Patterson*

Center for Molecular Toxicology and Carcinogenesis, Department of Veterinary and Biomedical Sciences, The Pennsylvania State University, University Park, Pennsylvania 16802, United States

ABSTRACT: The drug metabolism field has long recognized the beneficial and sometimes deleterious influence of microbiota in the absorption, distribution, metabolism, and excretion of drugs. Early pioneering work with the sulfanilamide precursor prontosil pointed toward the necessity not only to better understand the metabolic capabilities of the microbiota but also, importantly, to identify the specific microbiota involved in the generation and metabolism of drugs. However, technological limitations important for cataloging the microbiota community as well as for understanding and/or predicting their metabolic capabilities hindered progress. Current advances including mass spectrometry-based metabolite profiling as well as culture-independent sequence-based identification and functional analysis of microbiota have begun to shed light on microbial metabolism. In this review, case studies will be presented to highlight key aspects (e.g., microbiota identification,



metabolic function and prediction, metabolite identification, and profiling) that have helped to clarify how the microbiota might impact or be impacted by drug metabolism. Lastly, a perspective of the future of this field is presented that takes into account what important knowledge is lacking and how to tackle these problems.

CONTENTS

1. Introduction	Α
2. Detecting and Decoding Microbial Chatter	С
2.1. Signatures of Microbial Metabolism and	
Composition	С
2.2. Mass Spectrometry-Based Metabolite Iden-	
tification and Metabolomics	Е
2.3. Culture-Independent Sequencing-Based	
Analysis and Functional Prediction	F
3. Conclusions and Perspective	G
Author Information	G
Corresponding Author	G
Funding	G
Notes	G
Biographies	G
Abbreviations	Н
References	Н

1. INTRODUCTION

Bacteria living on and within our bodies make important metabolic contributions, whether it is extracting calories from the diet¹ or contributing to the metabolism of drugs.² While this review uses examples from bacteria involved in modulating (or being modulated by) drug metabolism in animal models and humans, many of the concepts can be applied to bacteria in symbiotic relationships or those in the environment that may encounter drugs or toxicants through deliberate application (e.g., pesticides) or through contamination (e.g., persistent

organic pollutants, antibiotics, and other drugs in wastewater). For example, a symbiotic and mutualistic relationship³ was recently clarified between the coffee berry borer (*Hypothenemus hampei*) and *Pseodomans fulva*, an important bacteria in the borer gut that permits it to survive in a caffeine-rich environment. Similarly, the bean bug, *Riptortus pedestris*, can degrade fenitrothion (an insecticide) through the metabolic activity of *Burkholderia* spp. in its gut.⁴ As will be discussed later, cutting-edge tools including 16S rRNA gene-based microbial community profiling, functional prediction, and mass spectrometry-based metabolite profiling were instrumental in identifying how these relationships benefit the host and the gut microbe.

From the discovery of prontosil as a precursor to the microbial-derived antibiotic sulfanilamide^{5,6} to a more recent example with the cardiac glycoside digoxin,⁷ research has only just scratched the surface of the incredibly complex and vital role that the microbiota can play both in terms of their contribution to pathologic conditions as well as serving as potential targets of (or sources of) therapeutic intervention. More than 50 years ago^{8–10} it was appreciated that the microbiota could perform biotransformation including hydrolysis, oxidation, reduction, and β -glucuronidase reactions and that drugs could also modulate the microbiota structure. For

Special Issue: Mass Spectrometry and Emerging Technologies for Biomarker Discovery in the Assessment of Human Health and Disease

Received: July 8, 2016

example, the microbiota substantially influences the metabolism of L-DOPA (levodopa, L-3,4-dihydroxyphenylalanine).¹¹ It was reported that following L-DOPA feeding to germ-free mice mhydroxyphenylacetic acid (m-HPAA) was not detected when urine extracts were analyzed via gas chromatography because the microbiota are needed to convert L-DOPA to m-tyramine, which is then converted to *m*-HPAA.¹¹ Thus, reduced metabolism of L-DOPA in germ-free mice greatly prolongs L-DOPA half-life and hence activity. This observation and others¹² are important when considering how the gut microbiota may promote adverse drug effects. Similarly, lactulose, a common treatment for constipation, was found to require several bacterial strains including Bacteroides and Bifidobacterium to metabolize lactulose into its therapeutic metabolites of lactic acid and acetic acid.¹³ An extensive table of drugs modulated by the microbiota has been reported elsewhere.14

A more recent example of how the gut microbiota influences drug metabolism is through studies of the anticancer drug irinotecan (CPT-11).^{15,16} Gut bacteria can "re-activate" glucuronidated drugs through their β -glucuronidase enzyme activity, and in the case of irinotecan, this process causes gut inflammation and irritation.^{15,16} The authors reported that partnering irinotecan with a β -glucuronidase inhibitor while not influencing serum levels of the activated drug decreased the amount of harmful metabolites produced from the bacteria, thus alleviating some of the gastrointestinal inflammation. This example also highlights the relationship between the gut microbiota and enterohepatic circulation, a process that has been recognized for decades.¹⁷ Bacterial β -glucuronidases are reported to be primary causes of nonsteroidal anti-inflammatory drugs (NSAID)-derived enteropathy.¹⁸ Similarly to irinotecan, glucuronidated NSAIDs are transported into the intestine via enterohepatic circulation where gut bacteria (in this¹⁸ example, *Escherichia coli*) will cleave the glucuronide, thus yielding harmful metabolites that cause the formation of ulcers in the gut.

Technology developments have significantly accelerated progress in the area of microbial-mediated drug metabolism. In order to illustrate how technology has greatly enhanced the discovery process with respect to microbiota-mediated drug metabolism, we highlight two examples: sodium cyclamate studies from the 1960s and recent studies with the cardiac glycoside digoxin.

Sodium cyclamate (sodium N-cyclohexanesulfamate) is an artificial sweetener that was shown to be metabolized to the potential human carcinogen cyclohexylamine, thus leading the FDA to ban it in 1970. Initial work by Kojima and Ichibagase¹⁹ identified the conversion of sodium cyclamate to cyclohexylamine, and later work suggested that this process was mediated by microbiota inhabiting the gastrointestinal tract.^{20,21} Here, only one volunteer (out of three total) fed a diet rich in sodium cyclamate produced high levels of cylohexylamine, demonstrating how gut microbiota contribute extensively to the metabolic phenotype or metabotype.²² Furthermore, the production of cyclohexylamine was dose-dependent.²³ Other reports demonstrated that rats could transfer the cyclohexylamine-producing capability to one another, likely through coprophagy, and that antibiotic treatment could dramatically reduce cyclohexylamine production.²⁴ Culture-based methods suggested that members of the Clostridia class were likely involved in the metabolic conversion in rats.²¹ It was also suggested that *Enterococci* could be responsible for the conversion from cyclamate to cyclohexylamine in humans.^{20,21} Along with the bacterial identification, two possible mechanisms were proposed. The first is a simple hydrolysis to remove the hydrogen sulfate ion, and the second is a hydrogen reduction to remove a bisulfite ion. Both mechanisms by Enterococci can yield cyclohexylamine. However, as was suggested by Scheline,¹⁰ many of these culturebased methods not only were limited in terms of what could be cultured but also were likely misleading given the inability to accurately identify the bacteria. Much of the metabolism work with sodium cyclamate was made possible by tracing the fate of ¹⁴C-labeled sodium cyclamate from tissues or cecal/fecal incubations using paper chromatography, radiochromatogram scanning, or gas chromatography coupled with chemical ionization mass spectrometry (GC-MS),^{25,26} all relatively sophisticated techniques at the time. Furthermore, Williams² lamented that metabolite identification studies were not only crucial to understanding the metabolic fate of drugs but also laborious and in some cases extremely challenging given the limited analytical chemistry resources available to investigators at the time.

Digoxin is a cardiac glycoside that is used worldwide for the treatment of atrial fibrillation and congenital heart failure. Its primary mechanism of action is through inhibition of Na-K-ATPase membrane pumps, thus increasing intracellular sodium levels; by means of compensation, the sodium calcium exchanger increases intracellular calcium to offset this effect. The result therefore is to increase cardiac output and systolic blood pressure as well as to slow the heart rate. Early observations²⁸ with digoxin suggested that indeed it too was metabolized by a member of the gut microbiota, Eggerthella lenta (previously Eubacterium lenta), to produce a metabolite that lacks cardiac activity (e.g., dihydrodigoxin, a digoxin reduction metabolite). Digoxin inactivation by gut microbiota was initially speculated and later confirmed in a series of elegant papers implicating E. lenta as the microbe responsible for generating the cardioinactive metabolites.²⁹ However, the mechanism by which digoxin is converted to dihydrodigoxin and other reduction products has only recently been established⁷ and importantly raises the possibility that patients might be identified based on their microbial populations as either potential responders or nonresponders to digoxin therapy. Haiser et al.' identified that the cgr operon within certain strains of E. lenta is induced and responsible for the reduction of digoxin using sophisticated RNA-seq analysis of microbiota gene expression. The authors proposed that this operon is intended to reduce fumarate in E. lenta; however, the unsaturated lactone present on the end of digoxin can also be used as a substrate for this operon. This results in saturation of the lactone, thus inactivating digoxin in the body. Furthermore, they used combinations of liquid chromatography coupled with mass spectrometry (LC-MS) and mutliple reaction monitoring (MRM) to carefully identify and quantitate the production of digoxin metabolites, capabilities that were simply not yet available to the cyclamate investigators (the triple quadrupole mass spectrometer was developed in 1978 by Enke and Yost of Michigan State University^{30,31}). The ease of use and increased senstivity of the new LC-MS/MS systems would have greatly hastened the study of sodium cyclamate metabolism.

In general, it is the combined use of sequence-based approaches as well as the functional, metabolic readouts provided by mass spectrometry-based metabolite profiling and metabolomics that have helped to reinvigorate the field of microbiota-mediated drug metabolism and accelerated



Figure 1. Metabolites produced or modified by the gut microbiota (i.e., metabolic chatter) can be studied using a variety of models and technological approaches. The contribution of the gut microbiota can be studied through comparisons of conventional and germ-free mice. Analyses of the gut microbiota can be achieved through culture-independent sequencing approaches like 16S rRNA gene sequencing, metagenomics, and/or metatranscriptomics. Reflections of the changes in gut microbial community structure and function as well as changes in host metabolism can be monitored by metabolomics.

discoveries in this space. Further unique mouse models including those lacking microbiota (herein referred to as germ-free mice) have provided new perspectives of the drug metabolism process^{32–34} and will likely urge not only the drug metabolism experts but also toxicologists to reconsider the impact of the microbiota on efficacy, potency, and toxicity.³⁵ In the following section, we discuss the concept of microbial metabolic chatter (Figure 1) and the essential tools required to listen in and decode these signals.

2. DETECTING AND DECODING MICROBIAL CHATTER

Small molecule "microbial chatter" can be used to describe how bacteria communicate with each other and with the host. For example, signaling networks based on quorum sensing molecules³⁶ can help a bacterial population sense its size as well as to prevent or limit the growth of competing populations. Microbial-generated metabolites or host metabolites acted upon by microbial metabolism (i.e., cometabolites) can interact with the host in a similar manner. Hence, the concept of small molecule "microbial chatter" represents a means by which the host and microbiota communicate, and this signaling network has just started to be unraveled through the application of mass spectrometry-based profiling and sequencing-based methods described below.

2.1. Signatures of Microbial Metabolism and Composition. Metabolomics can simply be defined as the process of identifying chemical fingerprints left behind by biological processes. Initially, the phrase "biological processes" most exclusively referred to those generated by the host, but numerous examples throughout the metabolomic literature suggest that microbiota-generated metabolites^{37–39} or host metabolites modified^{40–43} by the microbiota (also known as cometabolites) significantly "contaminate" the metabolomic signature. These observations have provided strong support for the use of metabolomics in the investigation of the microbiome. For example, 2,8-dihydroxyquinoline (2,8-DHQ) and its glucuronide (2,8-DHQ- β -D-Gluc) were found to be enriched (Table 1) in the urine of mice treated with the peroxisome proliferator-activated receptor alpha (PPAR α) agonist WY- 14,643.⁴⁴ Mice treated with the antioxidant tempol similarly have increased excretion of 2,8-DHQ and 2,8-DHQ- β -D-Gluc in their urine.³⁹ While never confirmed specifically in these studies to be of bacterial origin, Wikoff et al.³⁷ reported in a mass spectrometry-based metabolomics investigation of conventional (those with microbiota) and germ-free mice that DHQ production was highly dependent on the presence of bacteria. Others have reported that isomers of 2,8-DHQ, including 2,4-DHQ, are important quorum sensing molecules that may be involved in the pathogenicity of *Pseudomonas aeruginosa*, although it remains to be determined if 2,8-DHQ plays a similar quorum sensing role or which microbe is generating it.

Like 2,8-DHQ, other metabolites (Table 1) may likely serve as important indicators of changes in the composition and/or metabolic activity of the microbiota. For example, hippuric acid, the glycine conjugate of benzoic acid, has a strong connection with the gut microbiota, and its concentration in urine has been shown to be dramatically reduced in either germ-free mice or in mice treated with antibiotics.⁴⁵ p-Cresol, trimethylamine, trimethylamine N-oxide, and short chain fatty acids are similarly known to be produced by microbiota, and their concentrations can be perturbed following drug treatment (Table 1). A targeted profiling study⁴⁶ of urine collected from INTERMAP (INTERnational collaborative study of MAcronutrients, micronutrients, and blood Pressure) examined the gut microbial metabolites phenylacetylglutamine, 3-cresol sulfate, and hippuric acid in 4000 samples and identified unique signatures associated with age, race, and gender. The authors conclude that such approaches based on LC-MS/MS may serve as a rapid and convenient way to ascertain the physiologic state of the gut microbiota under various conditions. However, despite our capabilities of measuring their concentrations by LC-MS/MS, the identities of the bacteria responsible for generating these metabolites remain unknown.

Recent studies of bile acids are emblematic of how mass spectrometry and sequencing-based approaches of the microbiota can be instrumental in advancing our understanding of how metabolites signal between the host and the gut

metabolite	treatment	source	host	mechanism	significance	method	ref
TβMCA ^a	Tempol (antioxidant)	Intestinal tissue	Mice	Tempol reduces BSH ^b activity of <i>Latobacillus</i> , causing an accumulation of T/ β MCA ^a and inhibition of FXR ^c signaling, producing antiobesity effects	Potential target of antiobesity drugs	UHPLC-ESI- QTOFMS ^d	Fei Li, Nature Communica- tions, 2013 ³⁸
Hippuric acid	Rifaximin (PXR ^e ago- nist)	Intestinal tissue	Mice	Mice treated with antibiotic rifaximin showed decrease in microbial metabolites such as hippuric acid	Influence of gut microbiota on absorption and distribution of naringenin	HPLC-ESI- MS/MS	Naiara Orrego-Lagaron, Brit- ish Journal of Nutrition, 2015 ⁹⁰
	Wy-14643 ^g (PPAR α^h agonist)	Urine	Mice	$\mathrm{PPAR}\alpha^h$ agonist increased glycine conjugation of benzoic acid to hippuric acid	Urinary biomarkers of $PPAR\alpha^h$ activation as a result of gut microbiota	UHPLC- TOFMS ⁱ	Yueying Zhen, Molecular En- docrinology, 2009 ⁴⁴
<i>p</i> -cresol sulfate	Rifampin (PXR ^e ago- nist)	Urine	Humans	The bacterial metabolite of taurine, <i>p</i> -cresol, decreased with antibiotic rifampin administration	Potential drug-drug interac- tions of PXR ^e activators	UHPLC- TOFMS ⁱ ; GC-MS ⁱ	Bora Kim, Journal of Proteome Research, 2013 ⁹¹
	Taurine (amino sul- fonic acid)	Urine	Rats	Taurine supplementation caused an increased output of <i>p</i> -cresol sulfate, decreasing blood pressure in spontaneously hypertensive rats	Preventative effects in cardio- vascular disease	¹ H NMR ^{k}	Kazuki Akira, Journal of Phar- maceutical and Biomedical Analysis, 2013 ⁹²
	Acetaminophen (anti- pyretic)	Urine	Humans	Competitive O-sulfonation of p-cresol reduces capacity to sulfonate acetaminophen	Influence of gut bacteria on drug-induced responses in- volving sulfonation	¹ H NMR ^{k}	T. Andrew Clayton, <i>Proceed-</i> ings of the National Academy of Sciences, 2009 ⁹³
TMA ^l , TMAO'''	3,3-dimethyl-1-buta- nol (inhibits TMA ¹ lyase)	Liver, kid- ney, plas- ma, urine	Mice	3,3-dimethyl-1-but anol inhibition of TMA l lyase inhibits microbial production of TMA l reducing TMAO''' levels	Potential treatment of athero- sclerosis and other cardiome- tabolic diseases	LC-MS/MS ⁿ	Zeneng Wang, Cell, 2015 ⁹⁴
	L-carnitine (amino acid derivative)	Plasma	Humans	Oral L-carnitine is metabolized to TMA' by intestinal microbiota. Further metabolism produces $TMAO'''$. L-carnitine also decreases AGE^o levels	Protective properties on vascu- lar injuries in human patients on hemodialysis	GC ^p	Kei Fukami, Journal of Car- diovascular Pharmacology, 2015 ⁹⁵
SCFA ⁴	Oxidized ethyl-lino- leate (induces mu- cosal hypertrophy)	Intestinal tissue	Rats	Oxidized ethyl linoleate decreases cecal fermentation of dietary fiber, changing ${\rm SCFA}^q$ composition	SCFA ⁴ potential inhibition of growth or proliferation of tumor cells	GC ^p	Hiroshi Hara, Journal of Nu- trition, 1996 ⁹⁶
	Sericin (antioxidant)	Feces	Rats	Dietary sericin elevates cecal production of organic acids such as a cetate and n -butyrate in rats fed a high-fat diet	Sericin use as a prebiotic to improve colon health	GC^p	Yukako Okazaki, <i>Journal of</i> Nutrition, 2011 ⁹⁷
$SCFA^{q}$ (acetate)	B-GOS ^r (prebiotic oligosaccharide)	Feces	Humans	Fermentation analysis of B-GOS ⁷ in vitro revealed increases in acetate production correlated with increase in <i>Bifidobacterium</i> populations	Potential use of B-GOS ^r as a prebiotic to modulate gut microbiota poplation	GCP	Roberta Grimaldi, <i>British</i> Journal of Nutrition, 2016 ⁹⁸
SCFA ^q (propionate)	Aspartame (artificial, nonsaccharide sweetener)	Serum	Rats	Aspartame increased total bacteria, <i>Enterobacteriaceae</i> , and <i>Clostridium leptum</i> . Aspartame was rapidly metabolized and associated with elevations in propionate	Aspartame involvement in in- creased risk of metabolic diseases	¹ H NMR ^{k}	Marie Palmnäs, <i>PLoS One</i> , 2014 ⁹⁹
SCFA ^q ; phenol, <i>p</i> - cresol	Arabinoxylan-oligosac- charides (prebiotic)	Intestinal tissue	Humans	In vitro AXOS ^{$^{\circ}$} supplementation resulted in decreased production of toxic microbial degradation products, increased production of beneficial SCFA ^{<i>q</i>} , and long-term effect on colonic microbe community	Use of AXOS [°] as a prebiotic to modulate microbial metabo- lism in distal colon	GC^{p} ; HPLC ^t	Juan I. Sanchez, <i>Microbial</i> Biotechnology, 2009 ¹⁰⁰
2,8-dihydroxyquino- line	Tempol (antioxidant)	Urine	Mice	Tempol increased urinary excretion of 2,8-dihydroxyquinoline along with bacterially produced glucuronide metabolites	Tempol affects microbiota composition and microbial metabolism	LC-MS/MS ⁿ	Fei Li, Journal of Proteome Research, 2013 ³⁹
	Wy-14643 ^g (PPAR α^h agonist)	Urine	Mice	Activation of PPAR α^{h} increased excretion of 2,8-dihydroxyquinoline	Urinary biomarkers of $PPAR\alpha^h$ activation as a result of gut microbiota	UHPLC- TOFMS ⁱ	Yueying Zhen, Molecular En- docrinology, 2009 ⁴⁴

D

Table 1. Metabolites Modified or Produced by Gut Microbiota

^aTaurine β muricholic acid. ^bBile salt hydrolase. ^cFarnesoid X receptor. ^dUltra-high pressure liquid chromatography-electrospray ionization/quadrupole-time-of-flight mass spectrometry. ^ePregnane X receptor. ^JHigh-performance liquid chromatography electrospray ionization tandem mass spectrometry. ^SPrinixic Acid. ^hPeroxisome proliferator activated receptor alpha. ^UUltra-high pressure liquid chromatography time-of-flight mass spectrometry. ^JFrom magnetic resonance. ^JTrimethylamine. ^mTrimethylamine N-oxide. ⁿLiquid chromatography tandem mass spectrometry. ^SProton nuclear magnetic resonance. ^JTrimethylamine. ^mTrimethylamine. ^PHigh-pressure liquid chromatography tandem mass spectrometry. ^dShort chain fatty acid. ^TBimuno-galactooligosaccharides. ^sArabinoxylan-cligosaccharides. ^fHigh-pressure liquid chromatography.

Chemical Research in Toxicology

DOI: 10.1021/acs.chemrestox.6b00236 Chem. Res. Toxicol. XXXX, XXX, XXX–XXX

microbiota.^{38,41,42} Once thought simply as detergents to help solubilize fat and fat-soluble vitamins, our appreciation of the complex and varied signaling roles that bile acids can play has grown in large part due to mass spectrometry-based characterization of bile acid pools.⁴⁷ For example, a recent report based on a combination of ultra-high-pressure liquid chromatography (UHPLC) coupled with quadrupole time-of-flight mass spectrometry (QTOFMS) for broad profiling and targeted applications using UHPLC-MS/MS have identified 145 primary, secondary, and tertiary bile acid species.⁴⁸ It should be clearly noted that in the case of bile acids where there exist numerous positional and stereochemical isomers the strategic application of UHPLC has been instrumental in helping to chromatographically resolve the stereoisomers and thus permit accurate quantitation. The extensive and sensitive capabilities afforded by the latest mass spectrometry platforms have helped to accelerate our understanding for the varied roles that bile acids can play. For example, recent observations involving mice treated with antibiotics or the antioxidant tempol suggest that perturbing the microbiota can profoundly influence the gut microbiota community structure as well as its metabolic function.^{38,39,41,42,49} In these cases, the end result is a shift in the bile acid pool toward taurine conjugated bile acids (taurine conjugation predominates in mice), which in turn antagonize the farnesoid X receptor, a critical ligand activated nuclear receptor that regulates bile acid, glucose, and lipid metabolism.⁵⁰ Other examples of drugs that modulate or interact with the microbiota include the diabetes drug metformin⁵¹ and HMG CoA reductase inhibitor simvastatin.

It is important to note that in addition to mass spectrometry, sequence-based analysis of the microbiota not only is helping to elucidate how the microbiota are capable of metabolizing drugs and endogenous metabolites but also has been instrumental in identifying which bacteria are key to the process. In a recent report, Devlin and Fischbach elegantly describe a new biosynthetic pathway for bile acids modulated by the microbiota.⁵³ They identify a process by which gut microbiota including E. lenta and Rumincoccus gnavus can detoxify bile acids such as deoxycholic acid to their iso forms $(3\beta$ -hydroxy epimer), which they report are less cytotoxic to the bacteria, although differential effects on the host were not explored. Using computational approaches, they identified the nicotinamide-dependent 3α - and 3β -hydroxysteroid dehydrogenase genes in *E. lenta* and *R. gnavus*. This approach along with classic toxicity assays and enzyme kinetics highlights the value of sequence-based approaches in discovery efforts to better understand the metabolism associated with the microbiota.

2.2. Mass Spectrometry-Based Metabolite Identification and Metabolomics. One of the most critical processes in untargeted metabolomics studies is the identification of metabolites, which is a prerequisite to relating the quantitative metabolomics data to its underlying biochemical role. Nuclear magnetic resonance (NMR) spectroscopy (¹H and ¹³C) and MS coupled with either liquid or gas chromatography are the techniques most commonly used for the structural determination of metabolites. NMR offers several unique advantages, but it is hampered by an overall lack of sensitivity, as well as difficulties in working with complex multicomponent mixtures. GC-MS is still the most commonly used method for the identification of unknown compounds, but the advent of electrospray ionization and atmospheric pressure chemical ionization has resulted in LC-MS playing an increasingly important role in the identification and quantitation of metabolites. Others have expertly reviewed the strengths and weakness of these platforms. $^{22,54-56}$ High-resolution accurate mass spectrometry can provide elemental formulas for the intact molecule, but fragmentation of the intact molecule either in the ionization source or a combination of collision-induced dissociation (CID) and tandem mass spectrometry (MS/MS) is necessary to begin characterization of the structure of the precursor ion.⁵⁷ Comparison of the experimentally obtained product ion mass spectra with those in metabolite databases such as METLIN,⁵⁸ MassBank,⁵⁹ the Human Metabolome Database,^{60,61} and Lipid Maps⁶² is typically the first step in metabolite identification. An alternative and complementary approach is to tentatively identify the metabolites by interpretation of their product ion mass spectra, which is growing in popularity as new bioinformatic and visualizations tools are being developed. There are many examples of certain classes of metabolites having diagnostic fragment ions (e.g., m/z 184 for phosphatidylcholines, lyso-phosphatidylcholines, and sphingomyelins; m/z 241 for phosphatidylinositols; m/z 85 for acylcarnitines; m/z 97 for glucosinolates) or class characteristic neutral losses (e.g., losses of 141 Da for phosphatidylethanolamines, 87 Da for phosphatidylserines, and 176 Da for glucuronides), and these are helpful in determining tentative structures. Unfortunately, many compounds do not have readily recognizable diagnostic fragment ions, and the de novo identification of metabolites by interpretation of their product ion mass spectra is extremely time-consuming and challenging.⁶³ Furthermore, the extensive metabolic repertoire and diverse population of the microbiota further complicate metabolite discovery efforts.

Multistage mass spectrometry (MS^n) afforded by ion trap platforms is a powerful technique for assisting in the determination of structures from interpretation of mass spectral data, especially since the advent of precursor ion fingerprinting.^{64,65} Precursor ion fingerprinting is based on the premise that structurally similar compounds possess matching substructures, and these matching substructures produce matching product ion spectra. It relies on the probability of various possible decomposition products of an ion being independent of the ionization method, structure of the precursor ion, and the formation mechanism of the ion undergoing decomposition. Matching spectra of identical product ions can be acquired regardless of the original structure and MS^n stage.

Multistage Elemental Formula generator is a recently developed software package that uses the precursor product ion relations to extract the relevant data from multistage mass spectra.⁶⁴ It can be used in combination with high-resolution accurate MSⁿ to permit the unambiguous assignment of elemental formulas to fragment ions and to neutral losses, thereby facilitating the metabolite identification process. This fragmentation tree approach for the structural characterization of metabolites was used to successfully discriminate between the two isomeric prostaglandins PGE2 and PGD2 with 12 and 18 unique elemental formula paths, respectively.⁶⁴

Using a combination of the above analytical approaches, it is becoming more feasible to detect, identify, and quantitate metabolites that are derived or modified from the gut microbiota. Understanding the "metabolic chatter" of the gut microbiota can inform about disease progression and provide a better understanding for how modulating the gut microbiota can significantly impact the metabolome. Data analysis and database tools including the recently developed platform MS-



Figure 2. Understanding the complete contribution of the microbiome to drug metabolism as well as human health and disease can best be achieved through a combination of analytical techniques. 16S rRNA gene sequencing-based community analysis reveals the taxonomic profile of the gut and can be used to predict which metabolic pathways are modulated with the approaches including PICRUSt. Metabolomic analysis and carefully measured metabolite concentrations can be used to validate the pathways seen in PICRUSt. Relationships can then be drawn between specific bacterial changes and specific metabolite levels to better understand the metabolic contribution of the microbiota.

DIAL⁶⁶ will likely have a great impact on the identification of known metabolites but also will help with the identification of unknowns (using approaches like fragmentation trees described above). Short chain fatty acids (SCFAs) including butyric acid, acetic acid, and propionic acid (and other microbial cometabolites) have been a central focus with respect to microbial metabolic activity.⁶⁷ For example, it has been reported that colonocytes rely on butyric acid as an important nutrient source or that butyric acid can impact immune homeostasis.⁶⁷ Additionally, the gut microbiome can contribute to choline degradation. Sulfur reducing bacterial species like those in the class Clostridia can degrade choline into trimethylamine (TMA).⁶⁸ TMA can be further metabolized by hepatic flavin monooxygenase (FMO) to trimethylamine-Noxide (TMAO).⁶⁹ TMAO has recently been seen to have a direct relationship to cardiovascular disease and atherosclerosis. These examples highlight the interplay between the microbiome and the metabolome, thus demonstrating their importance for understanding disease progression.

2.3. Culture-Independent Sequencing-Based Analysis and Functional Prediction. Predicting the function of the microbiota (beyond standard census taking with 16S rRNA community profiling) is perhaps the ultimate objective in microbiome research. PICRUSt (Phylogenic Investigation of Communities by Reconstruction of Unobserved States) created by the Huttenhower lab in Harvard⁷⁰ is a bioinformatic application that infers metabolic information from 16S rRNA gene sequencing data. PICRUSt uses phylogenic trees created during 16S rRNA gene sequencing analysis to assign functional pathways to clades of bacteria.⁷⁰ A significant concern with this approach is lateral gene transfer, meaning that distantly related bacteria can share functionality, thus contradicting the idea that only bacterial clades share functionality.⁷⁰ The Huttenhower group accounted for this by incorporating ancestral state reconstruction algorithms that take into account the probability for initiation and reception of lateral gene transfer. For example, Lee and Ko investigated the effects of metformin on the gut microbiota using PICRUSt.⁷¹ In this report, they used five groups of mice including those only on a high-fat diet, those on a high-fat diet and treated with metformin, those on a high-fat diet that transitioned to a normal diet, those on a normal diet and treated with metformin, and those that were only on a normal diet.⁷¹ PICRUSt analysis identified that fatty acid metabolism of the gut microbiota was increased in the metformin-treated mice, which represents a potential explanation for the beneficial attributes of metformin therapy.⁷ Unfortunately, this group did not validate the PICRUSt results with mass spectrometry-based metabolomics or targeted profiling to quantitate fatty acid levels.

Along with PICRUSt, metagenomic studies can also be run in conjunction with metabolomics to show, and confirm, bacterial functionality. HUMAnN2 (HMP Unified Metabolic Analysis Network 2) is an analytical pathway that can be used to analyze the metagenomics sequence results.⁷² Like PICRUSt, HUMAnN2 investigates gut microbiome functionality. The major difference is that the HUMAnN2 pipeline uses metagenomic shotgun sequence reads from the Illumina Hiseq platform, whereas PICRUSt typically uses 16S rRNA gene sequencing reads from the Illumina Miseq. Whole genome sequencing involves sequencing bacterial DNA from a sample microbiome, whereas 16S rRNA gene sequencing only sequences the unique V4-V4 (or, depending on the application, other variable regions of the 16S rRNA gene) variable region of the bacterial genome. HUMAnN2 uses MetaPhlAn 2 (Metagenomic Phylogenetic Analysis 2) to assign taxonomy to the shotgun reads.⁷³ The HUMAnN2 algorithms

use the MetaCyc database to assign pathways and their relative abundances to each sample. An earlier version of HUMAnN2 was used in a recent study of antibiotic resistant genes in the fecal microbiome.⁷⁴ It was reported that short-term exposure to clindamycin and ciprofloxacin had a lasting impact on the fecal microbiome by drastically decreasing the amount of butyrate producing bacteria.⁷⁴ The oral microbiome was much more resilient and had less antibiotic resistance pathways than the fecal microbiome after exposure to antibiotics.⁷⁴ Other metagenomic studies have been performed using different software packages other than HUMAnN2. One of these studies uses MOCAT (Metagenomic Analysis Toolkit)⁷⁵ and CD-HIT⁷⁶ to investigate the effects of metformin on the gut microbiome.⁷⁷ The metagenomic study reported that metformin treatment caused an increase of Escherichia spp. in the gut which resulted in an increase of gas metabolism pathways, a common side effect of metformin.⁷⁷ While metagenomic studies can be time-consuming and computationally intensive, it remains an invaluable tool to help understand the functionality of the gut microbiota.

A recent framework for combining 16S rRNA sequencing, metagenomic data, and metabolomics data was described.⁷⁸ This framework associated metabolites with bacteria and monitored changes based on a disease state. While the concepts are indeed interesting, the incorporation of data from Illumina MiSeq or HiSeq would greatly enrich this approach and likely inform pharmacology and toxicology research. Developing new tools that integrate the vast and varied sources of data will likely provide incredibly informative and new perspectives by which to understand the impact of the gut microbiota on health and disease.

3. CONCLUSIONS AND PERSPECTIVE

It is clear that as the "forgotten organ"⁷⁹ the gut microbiota can significantly contribute to host metabolism in both beneficial and deleterious ways. Interest in the gut microbiota has been invigorated through technological advances in culture-independent sequence-based analysis of the microbiota as well as through mass spectrometry-based analysis and characterization of metabolites produced by or modified by the microbiota. As tools such as 16S rRNA gene sequencing, metagenomics, metatranscriptomics, and mass spectrometry-based metabolite profiling become commonplace, the integration of these different streams of data (Figure 2) will provide the most informative view of the microbiota's metabolic impact and function.^{80,81} Further models based on genome scale models that combine in silico models and data collected from sequencing and metabolomics approaches are becoming more commonplace and likely will permit more generalized models to be developed and new hypotheses to be tested.^{82,83} However, the bioinformatic tools necessary to handle and merge these data sets into a meaningful and comprehensive view of microbial metabolism remain an expanding and evolving area of science.

Tremendous efforts are currently underway to catalogue and characterize members of the human microbiome as part of the National Institutes of Health sponsored Human Microbiome Project.^{84,85} The project has helped generate incredible insight into the microbiome of healthy and diseased humans and has established new resources (e.g., databases of reference genomes, sequence tools, protocols) to help accelerate as well as to standardize research in this area. Similarly, the National Institutes of Health Common Fund has established regional

comprehensive metabolomics resource cores to increase accesibility to metabolite profiling services and resources.⁸⁶ As of yet, no formal integration of the two consortiums has been established, but as the fields progress, it seems likely that the microbiome and metabolomics research communities are destined for a long and productive relationship.

Lastly, it is important to consider not only the mechanisms by which the microbiota contribute to (or are themselves impacted by) drug metabolism but also how to incorporate this information when considering drug toxicity. This concept is even more important when considering how to develop therapeutics that target the microbiota and ultimately how to assess toxicity of the microbiota. Several recent examples suggest that known toxicants like the persistent organic pollutant and aryl hydrocarbon receptor activator, 2,3,7,8tetrachlorodibenzofuran,⁸⁷ or heavy metal arsenic^{88,85} can profoundly alter not only the gut microbiota community but also its metabolic function (e.g., changes in SCFA production). Futhermore, given that different disease states (e.g., obesity, diabetes) can impact the gut microbiota structure and function, how we will incorporate this information into drug toxicity assessment has yet to be determined. Clearly, biomarkers of microbome "health" and "toxicity" are required and will likely become important components of our overall understanding of drug and toxicant metabolism.

AUTHOR INFORMATION

Corresponding Author

*E-mail: adp117@psu.edu. Phone: 814-867-4565.

Funding

This work was supported in part by the following grants: ES0221896 (A.D.P.), CA124533 (J.M.P.), and CA140369 (J.M.P.) $\,$

Notes

The authors declare the following competing financial interest(s): Dr. Patterson owns equity in Heliome Biotech. This financial interest has been reviewed by the University's Individual Conflict of Interest Committees and is currently being managed by the University.

Biographies

Robert G. Nichols is a Molecular Toxicology graduate student at the Pennsylvania State University studying the interactions between the host and microbiota.

Nicole E. Hume is a Schreyer honors undergraduate student at the Pennsylvania State University majoring in Toxicology. Ms. Hume studies the impact that the gut microbiota have on ceramide synthesis.

Philip B. Smith is Director of Metabolomics at the Pennsylvania State University. Dr. Smith is an analytical chemist with extensive experience in the application of modern analytical chemistry techniques for the detection, identification, and quantitation of a wide variety of chemical and biochemical compounds. His work is focused on mass spectrometric applications, including the development and utilization of sensitive, compound-specific analytical methods; these methods often incorporate selective ionization and scanning techniques, resulting in the successful detection and identification of very low levels of compounds present in complex matrices.

Jeffrey M. Peters is Distinguished Professor and Associate Director of the Center for Molecular Toxicology and Carcinogenesis at the Pennsylvania State University. He has received a number of awards including The Society of Toxicology Achievement Award and The Huck Award for Outstanding Achievements in Life Sciences Research. Dr. Peters has performed seminal research focused on the biological role of the peroxisome proliferator-activated receptors (PPARs). His studies have provided clues to new molecular targets that may be suitable for the treatment and prevention of cancer.

Andrew D. Patterson is Associate Professor of Molecular Toxicology and Scientific Director of Metabolomics at the Pennsylvania State University. The Patterson lab studies the host metabolite—microbiome axis—specifically how the manipulation of gut bacteria through xenobiotic exposure impacts bile acid pools, their metabolism, and how they interact with host nuclear receptors. The lab employs a variety of cutting-edge tools including ¹H nuclear magnetic resonance spectroscopy and mass spectrometry-based metabolomics and conventional and gnotobiotic mouse models to facilitate its study of these pathways and understand their potential impact on human health and disease. A central question he and his lab are pursuing is how host nuclear receptors and the gut microbiota contribute to the development of nonalcoholic fatty liver disease.

ABBREVIATIONS

UHPLC-QTOFMS, ultra-high-pressure liquid chromatography coupled with quadrupole time-of-flight mass spectrometry; LC-MS, liquid chromatography coupled with mass spectrometry; GC-MS, gas chromatography coupled with mass spectrometry; MRM, mulitple reaction monitoring; NMR, nuclear magnetic resonance spectroscopy; SCFA, short chain fatty acid; PICRUSt, Phylogenic Investigation of Communities by Reconstruction of Unobserved States; INTERMAP, INTERnational collaborative study of MAcronutrients, micronutrients, and blood Pressure; MOCAT, MetagenOmiC Analysis Toolkit; MetaPhIAn, METAgenomic Phylogenetic Analysis; HU-MANN2, HMP Unified Metabolic Analysis Network; TMAO, trimethylamine-*N*-oxide; TMA, trimethylamine; FMO, flavin monooxygenase; MSⁿ, multistage mass spectrometry; 2,8-DHQ, 2,8-dihydroxyquinoline

REFERENCES

(1) Jumpertz, R., Le, D. S., Turnbaugh, P. J., Trinidad, C., Bogardus, C., Gordon, J. I., and Krakoff, J. (2011) Energy-balance studies reveal associations between gut microbes, caloric load, and nutrient absorption in humans. *Am. J. Clin. Nutr.* 94, 58–65.

(2) Spanogiannopoulos, P., Bess, E. N., Carmody, R. N., and Turnbaugh, P. J. (2016) The microbial pharmacists within us: a metagenomic view of xenobiotic metabolism. *Nat. Rev. Microbiol.* 14, 273–287.

(3) Ceja-Navarro, J. A., Vega, F. E., Karaoz, U., Hao, Z., Jenkins, S., Lim, H. C., Kosina, P., Infante, F., Northen, T. R., and Brodie, E. L. (2015) Gut microbiota mediate caffeine detoxification in the primary insect pest of coffee. *Nat. Commun.* 6, 7618.

(4) Kikuchi, Y., Hayatsu, M., Hosokawa, T., Nagayama, A., Tago, K., and Fukatsu, T. (2012) Symbiont-mediated insecticide resistance. *Proc. Natl. Acad. Sci. U. S. A. 109*, 8618–8622.

(5) Spink, W. W., Hurd, F. W., and Jermsta, J. (1940) In vitro conversion of prontosil-soluble to sulfanilamide by various types of microorganism. *Exp. Biol. Med.* 43, 172–175.

(6) Gingell, R., Bridges, J. W., and Williams, R. T. (1971) The role of the gut flora in the metabolism of prontosil and neoprontosil in the rat. *Xenobiotica* 1, 143–156.

(7) Haiser, H. J., Seim, K. L., Balskus, E. P., and Turnbaugh, P. J. (2014) Mechanistic insight into digoxin inactivation by Eggerthella lenta augments our understanding of its pharmacokinetics. *Gut Microbes 5*, 233–238.

(8) Williams, R. T. (1972) Toxicologic implications of biotransformation by intestinal microflora. *Toxicol. Appl. Pharmacol.* 23, 769–781. (9) Scheline, R. R. (1968) The metabolism of drugs and other organic compounds by the intestinal microflora. *Acta Pharmacol. Toxicol.* 26, 332–342.

(10) Scheline, R. R. (1968) Drug metabolism by intestinal microorganisms. *J. Pharm. Sci.* 57, 2021–2037.

(11) Goldin, B. R., Peppercorn, M. A., and Goldman, P. (1973) Contributions of host and intestinal microflora in the metabolism of Ldopa by the rat. *J. Pharmacol. Exp. Ther.* 186, 160–166.

(12) Li, H., He, J., and Jia, W. (2016) The influence of gut microbiota on drug metabolism and toxicity. *Expert Opin. Drug Metab. Toxicol.* 12, 31–40.

(13) Sahota, S. S., Bramley, P. M., and Menzies, I. S. (1982) The fermentation of lactulose by colonic bacteria. *Microbiology* 128, 319–325.

(14) Yip, L. Y., and Chan, E. C. (2015) Investigation of Host-Gut Microbiota Modulation of Therapeutic Outcome. *Drug Metab. Dispos.* 43, 1619–1631.

(15) Wallace, B. D., Roberts, A. B., Pollet, R. M., Ingle, J. D., Biernat, K. A., Pellock, S. J., Venkatesh, M. K., Guthrie, L., O'Neal, S. K., Robinson, S. J., Dollinger, M., Figueroa, E., McShane, S. R., Cohen, R. D., Jin, J., Frye, S. V., Zamboni, W. C., Pepe-Ranney, C., Mani, S., Kelly, L., and Redinbo, M. R. (2015) Structure and Inhibition of Microbiome beta-Glucuronidases Essential to the Alleviation of Cancer Drug Toxicity. *Chem. Biol.* 22, 1238–1249.

(16) Wallace, B. D., Wang, H., Lane, K. T., Scott, J. E., Orans, J., Koo, J. S., Venkatesh, M., Jobin, C., Yeh, L. A., Mani, S., and Redinbo, M. R. (2010) Alleviating cancer drug toxicity by inhibiting a bacterial enzyme. *Science* 330, 831–835.

(17) Clark, A. G., Fischer, L. J., Millburn, P., Smith, R. L., and Williams, R. T. (1969) The role of gut flora in the enterohepatic circulation of stilboestrol in the rat. *Biochem. J.* 112, 17P–18P.

(18) LoGuidice, A., Wallace, B. D., Bendel, L., Redinbo, M. R., and Boelsterli, U. A. (2012) Pharmacologic targeting of bacterial betaglucuronidase alleviates nonsteroidal anti-inflammatory drug-induced enteropathy in mice. *J. Pharmacol. Exp. Ther.* 341, 447–454.

(19) Kojima, S., and Ichibagase, H. (1966) Studies on synthetic sweetening agents. 8. Cyclohexylamine, a metabolite of sodium cyclamate. *Chem. Pharm. Bull.* 14, 971–974.

(20) Drasar, B. S., Renwick, A. G., and Williams, R. T. (1971) The conversion of cyclamate into cyclohexylamine by gut bacteria. *Biochem. J.* 123, 26P–27P.

(21) Drasar, B. S., Renwick, A. G., and Williams, R. T. (1972) The role of the gut flora in the metabolism of cyclamate. *Biochem. J.* 129, 881–890.

(22) Johnson, C. H., Patterson, A. D., Idle, J. R., and Gonzalez, F. J. (2012) Xenobiotic metabolomics: major impact on the metabolome. *Annu. Rev. Pharmacol. Toxicol.* 52, 37–56.

(23) Oser, B. L., Carson, S., Vogin, E. E., and Sonders, R. C. (1968) Conversion of cyclamate to cyclohexylamine in rats. *Nature 220*, 178– 179.

(24) Dalderup, L. M., Keller, G. H., and Schouten, F. (1970) Cyclamate and cyclohexylamine. *Lancet* 295, 845.

(25) Renwick, A. G., and Williams, R. T. (1969) Gut bacteria and the metabolism of cyclamate in the rat. *Biochem. J.* 114, 78P.

(26) Renwick, A. G., and Williams, R. T. (1972) The fate of cyclamate in man and other species. *Biochem. J.* 129, 869–879.

(27) Williams, R. T. (1951) The metabolism of drugs and toxic substances. *Annu. Rev. Biochem.* 20, 441–464.

(28) Saha, J. R., Butler, V. P., Jr., Neu, H. C., and Lindenbaum, J. (1983) Digoxin-inactivating bacteria: identification in human gut flora. *Science* 220, 325–327.

(29) Lindenbaum, J., Rund, D. G., Butler, V. P., Jr., Tse-Eng, D., and Saha, J. R. (1981) Inactivation of digoxin by the gut flora: reversal by antibiotic therapy. *N. Engl. J. Med.* 305, 789–794.

(30) Yost, R. A., and Enke, C. G. (1979) Triple quadrupole mass spectrometry for direct mixture analysis and structure elucidation. *Anal. Chem.* 51, 1251–1264.

(31) Yost, R. A., and Enke, C. G. (1978) Selected ion fragmentation with a tandem quadrupole mass spectrometer. J. Am. Chem. Soc. 100, 2274–2275.

(32) Selwyn, F. P., Cheng, S. L., Bammler, T. K., Prasad, B., Vrana, M., Klaassen, C., and Cui, J. Y. (2015) Developmental Regulation of Drug-Processing Genes in Livers of Germ-Free Mice. *Toxicol. Sci.* 147, 84–103.

(33) Selwyn, F. P., Cheng, S. L., Klaassen, C. D., and Cui, J. Y. (2016) Regulation of Hepatic Drug-Metabolizing Enzymes in Germ-Free Mice by Conventionalization and Probiotics. *Drug Metab. Dispos.* 44, 262–274.

(34) Selwyn, F. P., Cui, J. Y., and Klaassen, C. D. (2015) RNA-Seq Quantification of Hepatic Drug Processing Genes in Germ-Free Mice. *Drug Metab. Dispos.* 43, 1572–1580.

(35) Dietert, R. R., and Silbergeld, E. K. (2015) Biomarkers for the 21st century: listening to the microbiome. *Toxicol. Sci.* 144, 208–216.

(36) Phelan, V. V., Liu, W. T., Pogliano, K., and Dorrestein, P. C. (2011) Microbial metabolic exchange-the chemotype-to-phenotype link. *Nat. Chem. Biol.* 8, 26–35.

(37) Wikoff, W. R., Anfora, A. T., Liu, J., Schultz, P. G., Lesley, S. A., Peters, E. C., and Siuzdak, G. (2009) Metabolomics analysis reveals large effects of gut microflora on mammalian blood metabolites. *Proc. Natl. Acad. Sci. U. S. A.* 106, 3698–3703.

(38) Li, F., Jiang, C., Krausz, K. W., Li, Y., Albert, I., Hao, H., Fabre, K. M., Mitchell, J. B., Patterson, A. D., and Gonzalez, F. J. (2013) Microbiome remodelling leads to inhibition of intestinal farnesoid X receptor signalling and decreased obesity. *Nat. Commun.* 4, 2384.

(39) Li, F., Pang, X., Krausz, K. W., Jiang, C., Chen, C., Cook, J. A., Krishna, M. C., Mitchell, J. B., Gonzalez, F. J., and Patterson, A. D. (2013) Stable isotope- and mass spectrometry-based metabolomics as tools in drug metabolism: a study expanding tempol pharmacology. *J. Proteome Res.* 12, 1369–1376.

(40) Swann, J. R., Tuohy, K. M., Lindfors, P., Brown, D. T., Gibson, G. R., Wilson, I. D., Sidaway, J., Nicholson, J. K., and Holmes, E. (2011) Variation in antibiotic-induced microbial recolonization impacts on the host metabolic phenotypes of rats. *J. Proteome Res. 10*, 3590–3603.

(41) Jiang, C., Xie, C., Li, F., Zhang, L., Nichols, R. G., Krausz, K. W., Cai, J., Qi, Y., Fang, Z. Z., Takahashi, S., Tanaka, N., Desai, D., Amin, S. G., Albert, I., Patterson, A. D., and Gonzalez, F. J. (2015) Intestinal farnesoid X receptor signaling promotes nonalcoholic fatty liver disease. J. Clin. Invest. 125, 386–402.

(42) Sayin, S. I., Wahlstrom, A., Felin, J., Jantti, S., Marschall, H. U., Bamberg, K., Angelin, B., Hyotylainen, T., Oresic, M., and Backhed, F. (2013) Gut microbiota regulates bile acid metabolism by reducing the levels of tauro-beta-muricholic acid, a naturally occurring FXR antagonist. *Cell Metab.* 17, 225–235.

(43) Swann, J. R., Want, E. J., Geier, F. M., Spagou, K., Wilson, I. D., Sidaway, J. E., Nicholson, J. K., and Holmes, E. (2011) Systemic gut microbial modulation of bile acid metabolism in host tissue compartments. *Proc. Natl. Acad. Sci. U. S. A. 108*, 4523–4530.

(44) Zhen, Y., Krausz, K. W., Chen, C., Idle, J. R., and Gonzalez, F. J. (2007) Metabolomic and genetic analysis of biomarkers for peroxisome proliferator-activated receptor alpha expression and activation. *Mol. Endocrinol.* 21, 2136–2151.

(45) Lees, H. J., Swann, J. R., Wilson, I. D., Nicholson, J. K., and Holmes, E. (2013) Hippurate: the natural history of a mammalianmicrobial cometabolite. *J. Proteome Res.* 12, 1527–1546.

(46) Wijeyesekera, A., Clarke, P. A., Bictash, M., Brown, I. J., Fidock, M., Ryckmans, T., Yap, I. K., Chan, Q., Stamler, J., Elliott, P., Holmes, E., and Nicholson, J. K. (2012) Quantitative UPLC-MS/MS analysis of the gut microbial co-metabolites phenylacetylglutamine, 4-cresyl sulphate and hippurate in human urine: INTERMAP Study. *Anal. Methods* 4, 65–72.

(47) Wahlstrom, A., Sayin, S. I., Marschall, H. U., and Backhed, F. (2016) Intestinal Crosstalk between Bile Acids and Microbiota and Its Impact on Host Metabolism. *Cell Metab.* 24, 41–50.

(48) Sarafian, M. H., Lewis, M. R., Pechlivanis, A., Ralphs, S., McPhail, M. J., Patel, V. C., Dumas, M. E., Holmes, E., and Nicholson, J. K. (2015) Bile acid profiling and quantification in biofluids using ultra-performance liquid chromatography tandem mass spectrometry. *Anal. Chem.* 87, 9662–9670.

(49) Cai, J., Zhang, L., Jones, R. A., Correll, J. B., Hatzakis, E., Smith, P. B., Gonzalez, F. J., and Patterson, A. D. (2016) Antioxidant Drug Tempol Promotes Functional Metabolic Changes in the Gut Microbiota. *J. Proteome Res.* 15, 563–571.

(50) Gonzalez, F. J., Jiang, C., and Patterson, A. D. (2016) An Intestinal Microbiota-Farnesoid X Receptor Axis Modulates Metabolic Disease. *Gastroenterology*, DOI: 10.1053/j.gastro.2016.08.057.

(51) Lee, H., and Ko, G. (2014) Effect of metformin on metabolic improvement and gut microbiota. *Appl. Environ. Microbiol.* 80, 5935–5943.

(52) Aura, A. M., Mattila, I., Hyotylainen, T., Gopalacharyulu, P., Bounsaythip, C., Oresic, M., and Oksman-Caldentey, K. M. (2011) Drug metabolome of the simvastatin formed by human intestinal microbiota in vitro. *Mol. BioSyst.* 7, 437–446.

(53) Devlin, A. S., and Fischbach, M. A. (2015) A biosynthetic pathway for a prominent class of microbiota-derived bile acids. *Nat. Chem. Biol.* 11, 685–690.

(54) Patterson, A. D., Gonzalez, F. J., and Idle, J. R. (2010) Xenobiotic metabolism: a view through the metabolometer. *Chem. Res. Toxicol.* 23, 851–860.

(55) Goodacre, R. (2007) Metabolomics of a superorganism. J. Nutr. 137, 259S-266S.

(56) Dettmer, K., Aronov, P. A., and Hammock, B. D. (2007) Mass spectrometry-based metabolomics. *Mass Spectrom. Rev.* 26, 51–78.

(57) Kind, T., and Fiehn, O. (2010) Advances in structure elucidation of small molecules using mass spectrometry. *Bioanal Rev.* 2, 23–60.

(58) Smith, C. A., O'Maille, G., Want, E. J., Qin, C., Trauger, S. A., Brandon, T. R., Custodio, D. E., Abagyan, R., and Siuzdak, G. (2005) METLIN: a metabolite mass spectral database. *Ther. Drug Monit.* 27, 747–751.

(59) Horai, H., Arita, M., Kanaya, S., Nihei, Y., Ikeda, T., Suwa, K., Ojima, Y., Tanaka, K., Tanaka, S., Aoshima, K., Oda, Y., Kakazu, Y., Kusano, M., Tohge, T., Matsuda, F., Sawada, Y., Hirai, M. Y., Nakanishi, H., Ikeda, K., Akimoto, N., Maoka, T., Takahashi, H., Ara, T., Sakurai, N., Suzuki, H., Shibata, D., Neumann, S., Iida, T., Tanaka, K., Funatsu, K., Matsuura, F., Soga, T., Taguchi, R., Saito, K., and Nishioka, T. (2010) MassBank: a public repository for sharing mass spectral data for life sciences. *J. Mass Spectrom.* 45, 703–714.

(60) Wishart, D. S., Jewison, T., Guo, A. C., Wilson, M., Knox, C., Liu, Y., Djoumbou, Y., Mandal, R., Aziat, F., Dong, E., Bouatra, S., Sinelnikov, I., Arndt, D., Xia, J., Liu, P., Yallou, F., Bjorndahl, T., Perez-Pineiro, R., Eisner, R., Allen, F., Neveu, V., Greiner, R., and Scalbert, A. (2013) HMDB 3.0–The Human Metabolome Database in 2013. *Nucleic Acids Res.* 41, D801–807.

(61) Wishart, D. S., Knox, C., Guo, A. C., Eisner, R., Young, N., Gautam, B., Hau, D. D., Psychogios, N., Dong, E., Bouatra, S., Mandal, R., Sinelnikov, I., Xia, J., Jia, L., Cruz, J. A., Lim, E., Sobsey, C. A., Shrivastava, S., Huang, P., Liu, P., Fang, L., Peng, J., Fradette, R., Cheng, D., Tzur, D., Clements, M., Lewis, A., De Souza, A., Zuniga, A., Dawe, M., Xiong, Y., Clive, D., Greiner, R., Nazyrova, A., Shaykhutdinov, R., Li, L., Vogel, H. J., and Forsythe, I. (2009) HMDB: a knowledgebase for the human metabolome. *Nucleic Acids Res.* 37, D603–610.

(62) Sud, M., Fahy, E., Cotter, D., Dennis, E. A., and Subramaniam, S. (2012) LIPID MAPS-Nature Lipidomics Gateway: An Online Resource for Students and Educators Interested in Lipids. *J. Chem. Educ.* 89, 291–292.

(63) Zhou, J., Weber, R. J., Allwood, J. W., Mistrik, R., Zhu, Z., Ji, Z., Chen, S., Dunn, W. B., He, S., and Viant, M. R. (2014) HAMMER: automated operation of mass frontier to construct in silico mass spectral fragmentation libraries. *Bioinformatics* 30, 581–583.

(64) Kasper, P. T., Rojas-Cherto, M., Mistrik, R., Reijmers, T., Hankemeier, T., and Vreeken, R. J. (2012) Fragmentation trees for the structural characterisation of metabolites. *Rapid Commun. Mass Spectrom. 26*, 2275–2286. (65) Sheldon, M. T., Mistrik, R., and Croley, T. R. (2009) Determination of ion structures in structurally related compounds using precursor ion fingerprinting. *J. Am. Soc. Mass Spectrom.* 20, 370–376.

(66) Tsugawa, H., Cajka, T., Kind, T., Ma, Y., Higgins, B., Ikeda, K., Kanazawa, M., VanderGheynst, J., Fiehn, O., and Arita, M. (2015) MS-DIAL: data-independent MS/MS deconvolution for comprehensive metabolome analysis. *Nat. Methods* 12, 523–526.

(67) Kim, M. H., Kang, S. G., Park, J. H., Yanagisawa, M., and Kim, C. H. (2013) Short-chain fatty acids activate GPR41 and GPR43 on intestinal epithelial cells to promote inflammatory responses in mice. *Gastroenterology* 145, 396–406.

(68) Craciun, S., and Balskus, E. P. (2012) Microbial conversion of choline to trimethylamine requires a glycyl radical enzyme. *Proc. Natl. Acad. Sci. U. S. A. 109*, 21307–21312.

(69) Wang, Z., Klipfell, E., Bennett, B. J., Koeth, R., Levison, B. S., Dugar, B., Feldstein, A. E., Britt, E. B., Fu, X., Chung, Y. M., Wu, Y., Schauer, P., Smith, J. D., Allayee, H., Tang, W. H., DiDonato, J. A., Lusis, A. J., and Hazen, S. L. (2011) Gut flora metabolism of phosphatidylcholine promotes cardiovascular disease. *Nature* 472, 57–63.

(70) Langille, M., Zaneveld, J., Caporaso, J. G., McDonald, D., Knights, D., Reyes, J., Clemente, J., Burkepile, D., Vega Thurber, R., Knight, R., Beiko, R., and Huttenhower, C. (2013) Predictive functional profiling of microbial communities using 16S rRNA marker gene sequences. *Nat. Biotechnol.* 31, 814–821.

(71) Lee, H., and Ko, G. (2014) Effect of Metformin on Metabolic Improvement and Gut Microbiota. *Appl. Environ. Microbiol.* 80, 5935–5943.

(72) Abubucker, S., Segata, N., Goll, J., Schubert, A. M., Izard, J., Cantarel, B. L., Rodriguez-Mueller, B., Zucker, J., Thiagarajan, M., Henrissat, B., White, O., Kelley, S. T., Methé, B., Schloss, P. D., Gevers, D., Mitreva, M., and Huttenhower, C. (2012) Metabolic reconstruction for metagenomic data and its application to the human microbiome. *PLoS Comput. Biol. 8*, e1002358.

(73) Truong, D. T., Franzosa, E. A., Tickle, T. L., Scholz, M., Weingart, G., Pasolli, E., Tett, A., Huttenhower, C., and Segata, N. (2015) MetaPhlAn2 for enhanced metagenomic taxonomic profiling. *Nat. Methods* 12, 902–903.

(74) Zaura, E., Brandt, B. W., de Mattos, M. J. T., Buijs, M. J., Caspers, M. P. M., Rashid, M. U., Weintraub, A., Nord, C. E., Savell, A., Hu, Y., Coates, A. R., Hubank, M., Spratt, D. A., Wilson, M., Keijser, B. J. F., and Crielaard, W. (2015) Same Exposure but two radically different responses to antibiotics: Resilience of the salivary microbiome versus long-term microbial shifts in feces. *mBio* 6, e01693-15.

(75) Kultima, J. R., Coelho, L. P., Forslund, K., Huerta-Cepas, J., Li, S. S., Driessen, M., Voigt, A. Y., Zeller, G., Sunagawa, S., and Bork, P. (2016) MOCAT2: a metagenomic assembly, annotation and profiling framework. *Bioinformatics* 32, 2520.

(76) Li, W., and Godzik, A. (2006) Cd-hit: A fast program for clustering and comparing large sets of protein or nucleotide sequences. *Bioinformatics* 22, 1658–1659.

(77) Forslund, K., Hildebrand, F., Nielsen, T., Falony, G., et al. (2015) Disentangling the effects of type 2 diabetes and metformin on the human gut microbiota. *Nature 528, 262–266.*

(78) Noecker, C., Eng, A., Srinivasan, S., Theriot, C. M., Young, V. B., Jansson, J. K., Fredricks, D. N., and Borenstein, E. (2016) Metabolic Model-Based Integration of Microbiome Taxonomic and Metabolomic Profiles Elucidates Mechanistic Links between Ecological and Metabolic Variation. *mSystems 1*, e00013-15.

(79) O'Hara, A. M., and Shanahan, F. (2006) The gut flora as a forgotten organ. *EMBO Rep.* 7, 688–693.

(80) Aguiar-Pulido, V., Huang, W., Suarez-Ulloa, V., Cickovski, T., Mathee, K., and Narasimhan, G. (2016) Metagenomics, Metatranscriptomics, and Metabolomics Approaches for Microbiome Analysis. *Evol. Bioinf. Online* 12, 5–16.

(81) Turnbaugh, P. J., and Gordon, J. I. (2008) An invitation to the marriage of metagenomics and metabolomics. *Cell* 134, 708–713.

(82) Zhang, L., Xie, C., Nichols, R. G., Chan, S. H. J., Jiang, C., Hao, R., Smith, P. B., Cai, J., Simons, M. N., Hatzakis, E., Maranas, C. D., Gonzalez, F. J., and Patterson, A. D. (2016) Farnesoid X Receptor Signaling Shapes the Gut Microbiota and Controls Hepatic Lipid Metabolism. *mSystems 1*, e00070-16.

(83) Mardinoglu, A., Shoaie, S., Bergentall, M., Ghaffari, P., Zhang, C., Larsson, E., Backhed, F., and Nielsen, J. (2015) The gut microbiota modulates host amino acid and glutathione metabolism in mice. *Mol. Syst. Biol.* 11, 834.

(84) Turnbaugh, P. J., Ley, R. E., Hamady, M., Fraser-Liggett, C. M., Knight, R., and Gordon, J. I. (2007) The human microbiome project. *Nature* 449, 804–810.

(85) Proctor, L. M. (2016) The National Institutes of Health Human Microbiome Project. *Semin. Fetal Neonatal Med.*, DOI: 10.1016/j.siny.2016.05.002.

(86) Sud, M., Fahy, E., Cotter, D., Azam, K., Vadivelu, I., Burant, C., Edison, A., Fiehn, O., Higashi, R., Nair, K. S., Sumner, S., and Subramaniam, S. (2016) Metabolomics Workbench: An international repository for metabolomics data and metadata, metabolite standards, protocols, tutorials and training, and analysis tools. *Nucleic Acids Res.* 44, D463–470.

(87) Zhang, L., Nichols, R. G., Correll, J., Murray, I. A., Tanaka, N., Smith, P. B., Hubbard, T. D., Sebastian, A., Albert, I., Hatzakis, E., Gonzalez, F. J., Perdew, G. H., and Patterson, A. D. (2015) Persistent Organic Pollutants Modify Gut Microbiota-Host Metabolic Homeostasis in Mice Through Aryl Hydrocarbon Receptor Activation. *Environ. Health Perspect.* 123, 679–688.

(88) Lu, K., Abo, R. P., Schlieper, K. A., Graffam, M. E., Levine, S., Wishnok, J. S., Swenberg, J. A., Tannenbaum, S. R., and Fox, J. G. (2014) Arsenic exposure perturbs the gut microbiome and its metabolic profile in mice: an integrated metagenomics and metabolomics analysis. *Environ. Health Perspect.* 122, 284–291.

(89) Lu, K., Mahbub, R., Cable, P. H., Ru, H., Parry, N. M., Bodnar, W. M., Wishnok, J. S., Styblo, M., Swenberg, J. A., Fox, J. G., and Tannenbaum, S. R. (2014) Gut microbiome phenotypes driven by host genetics affect arsenic metabolism. *Chem. Res. Toxicol.* 27, 172–174.

(90) Orrego-Lagaron, N., Martinez-Huelamo, M., Vallverdu-Queralt, A., Lamuela-Raventos, R. M., and Escribano-Ferrer, E. (2015) High gastrointestinal permeability and local metabolism of naringenin: influence of antibiotic treatment on absorption and metabolism. *Br. J. Nutr.* 114, 169–180.

(91) Kim, B., Moon, J.-Y., Choi, M. H., Yang, H. H., Lee, S. H., Lim, K. S., Yoon, S. H., Yu, K.-S., Jang, I.-J., and Cho, J.-Y. (2013) Global Metabolomics and Targeted Steroid Profiling Reveal That Rifampin, a Strong Human PXR Activator, Alters Endogenous Urinary Steroid Markers. *J. Proteome Res.* 12 (3), 1359–1368.

(92) Akira, K., Hichiya, H., Morita, M., Shimizu, A., and Mitome, H. (2013) Metabonomic study on the biochemical response of spontaneously hypertensive rats to chronic taurine supplementation using ¹H NMR spectroscopic urinalysis. *J. Pharm. Biomed. Anal.* 85, 155–161.

(93) Clayton, T. A., Baker, D., Lindon, J. C., Everett, J. R., and Nicholson, J. K. (2009) Pharmacometabonomic identification of a significant host-microbiome metabolic interaction affecting human drug metabolism. *Proc. Natl. Acad. Sci. U. S. A. 106*, 14728–14733.

(94) Wang, Z., Roberts, A. B., Buffa, J. A., Levison, B. S., Zhu, W., Org, E., Gu, X., Huang, Y., Zamanian-Daryoush, M., Culley, M. K., DiDonato, A. J., Fu, X., Hazen, J. E., Krajcik, D., DiDonato, J. A., Lusis, A. J., and Hazen, S. L. (2015) Non-lethal Inhibition of Gut Microbial Trimethylamine Production for the Treatment of Atherosclerosis. *Cell 163*, 1585–1595.

(95) Fukami, K., Yamagishi, S.-i., Sakai, K., Kaida, Y., Yokoro, M., Ueda, S., Wada, Y., Takeuchi, M., Shimizu, M., Yamazaki, H., and Okuda, S. (2015) Oral L-carnitine supplementation increases trimethylamine-N-oxide but reduces markers of vascular injury in hemodialysis patients. J. Cardiovasc. Pharmacol. 65, 289–295.

(96) Hara, H., Miyashita, K., Ito, S., and Kasai, T. (1996) Oxidized ethyl linoleate induces mucosal hypertrophy of the large intestine and

affects cecal fermentation of dietary fiber in rats. J. Nutr. 126, 800–806. (97) Okazaki, Y., Tomotake, H., Tsujimoto, K., Sasaki, M., and Kato, N. (2011) Consumption of a resistant protein, sericin, elevates fecal immunoglobulin A, mucins, and cecal organic acids in rats fed a high-

fat diet. J. Nutr. 141, 1975–1981. (98) Grimaldi, R., Swann, J. R., Vulevic, J., Gibson, G. R., and Costabile, A. (2016) Fermentation properties and potential prebiotic activity of Bimuno galacto-oligosaccharide (65 % galacto-oligosaccharide content) on in vitro gut microbiota parameters. Br. J. Nutr. 116, 480–486.

(99) Palmnas, M. S. A., Cowan, T. E., Bomhof, M. R., Su, J., Reimer, R. A., Vogel, H. J., Hittel, D. S., and Shearer, J. (2014) Low-dose aspartame consumption differentially affects gut microbiota-host metabolic interactions in the diet-induced obese rat. *PLoS One 9*, e109841.

(100) Sanchez, J. I., Marzorati, M., Grootaert, C., Baran, M., Van Craeyveld, V., Courtin, C. M., Broekaert, W. F., Delcour, J. A., Verstraete, W., and Van de Wiele, T. (2009) Arabinoxylanoligosaccharides (AXOS) affect the protein/carbohydrate fermentation balance and microbial population dynamics of the Simulator of Human Intestinal Microbial Ecosystem. *Microb. Biotechnol.* 2, 101– 113.